Bitcoin Price Prediction using Machine Learning

Problem Statement:

Machine learning enables automation in various fields, including trading, by predicting profitable trades. This project focuses on building a model using historical data to improve decision-making and reduce financial risks. We will use different libraries for data processing, visualization, and model training. 🚀

In [1]:
```
# Import necessary libraries
import numpy as np  # NumPy for numerical operations
import pandas as pd  # Pandas for data manipulation and analysis
import matplotlib.pyplot as plt  # Matplotlib for data visualization
import seaborn as sns  # Seaborn for enhanced visualizations
import warnings  # Warnings module to handle unnecessary warning messages

# Suppress warnings for a cleaner output
warnings.filterwarnings('ignore')
```

In [2]:
```
# Load the dataset from a CSV file
df = pd.read_csv('bitcoin_data.csv')

# Inspect the dataset
print("First 5 rows of the dataset:")
print(df.head())  # Display the first 5 rows of the dataset
```

```
First 5 rows of the dataset:
         Date      Price       Open       High        Low     Vol. Change %
0  10-03-2025  79,812.10  80,702.20  83,902.80  79,264.30  105.70K   -1.09%
1  09-03-2025  80,691.60  86,221.50  86,498.60  80,048.90   69.90K   -6.41%
2  08-03-2025  86,221.90  86,783.80  86,886.80  85,264.60   41.90K   -0.36%
3  07-03-2025  86,531.20  89,879.50  91,059.80  84,864.30  138.11K   -3.78%
4  06-03-2025  89,930.90  90,611.70  92,802.00  87,849.60   89.27K   -0.75%
```

In [3]:
```
print("\nDataset Info:")
df.info()  # Display summary information about the dataset (column names, da
```

```
Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1529 entries, 0 to 1528
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   Date      1529 non-null   object
 1   Price     1529 non-null   object
 2   Open      1522 non-null   object
 3   High      1529 non-null   object
 4   Low       1525 non-null   object
 5   Vol.      1529 non-null   object
 6   Change %  1529 non-null   object
dtypes: object(7)
memory usage: 83.7+ KB
```

In [4]:

```
print("\nDataset Shape:", df.shape)  # Print the number of rows and columns
```

```
Dataset Shape: (1529, 7)
```

In [5]:

```
print("\nSummary Statistics:")
print(df.describe(include='all'))  # Display statistical summary, including
```

```
Summary Statistics:
              Date      Price       Open       High        Low    Vol.  \
count         1529       1529       1522       1529       1525    1529   
unique        1529       1525       1517       1525       1524    1480   
top     01-01-2021  21,517.20  29,912.70  40,599.00  34,357.40  56.24K   
freq             1          2          2          2          2       3   

       Change %  
count      1529  
unique      820  
top      -0.03%  
freq          7  
```

In [6]:

```
df.columns
```

Out[6]:

```
Index(['Date', 'Price', 'Open', 'High', 'Low', 'Vol.', 'Change %'], dtype
='object')
```

Data Cleaning

Handling Missing Values

In [7]:

```
# Check for missing values
print("\nMissing values in each column:")  # Print a message for clarity
print(df.isnull().sum()/len(df)*100)  # Display the count of missing values
```

```
Missing values in each column:
Date        0.000000
Price       0.000000
Open        0.457816
High        0.000000
Low         0.261609
Vol.        0.000000
Change %    0.000000
dtype: float64
```

In [8]:
```
# Handle missing values
df.dropna(inplace=True)  # Drop any rows that contain missing values
```

In [9]:
```
# Check again if any missing values remain after cleaning
print("\nMissing values after cleaning:")
print(df.isnull().sum())  # Display the count of missing values after handli
```

```
Missing values after cleaning:
Date        0
Price       0
Open        0
High        0
Low         0
Vol.        0
Change %    0
dtype: int64
```

In [10]:
```
# Convert relevant columns to numeric type
# The dataset contains values with commas and percentage signs, so they need

# Convert 'Price' column from string to numeric, removing commas
df['Price'] = pd.to_numeric(df['Price'].str.replace(',', ''), errors='coerce
```

In [11]:
```
# Convert 'Open' column from string to numeric, removing commas
df['Open'] = pd.to_numeric(df['Open'].str.replace(',', ''), errors='coerce')
```

In [12]:
```
# Convert 'High' column from string to numeric, removing commas
df['High'] = pd.to_numeric(df['High'].str.replace(',', ''), errors='coerce')
```

In [13]:
```
# Convert 'Low' column from string to numeric, removing commas
df['Low'] = pd.to_numeric(df['Low'].str.replace(',', ''), errors='coerce')
```

In [14]:
```
# Convert 'Vol.' column by replacing 'K' with 'e3' (thousands) and 'M' with
df['Vol.'] = df['Vol.'].str.replace('K', 'e3').str.replace('M', 'e6')
```

In [15]:
```
# Convert 'Vol.' column from string to numeric (after conversion of K/M suff
df['Vol.'] = pd.to_numeric(df['Vol.'], errors='coerce')
```

In [16]:
```
# Convert 'Change %' column by removing '%' and converting it to decimal (e.
df['Change %'] = df['Change %'].str.replace('%', '').astype(float) / 100
```

In [17]:
```
# Convert 'Date' column from string format to proper datetime format
df['Date'] = pd.to_datetime(df['Date'], format='%d-%m-%Y', errors='coerce')
```

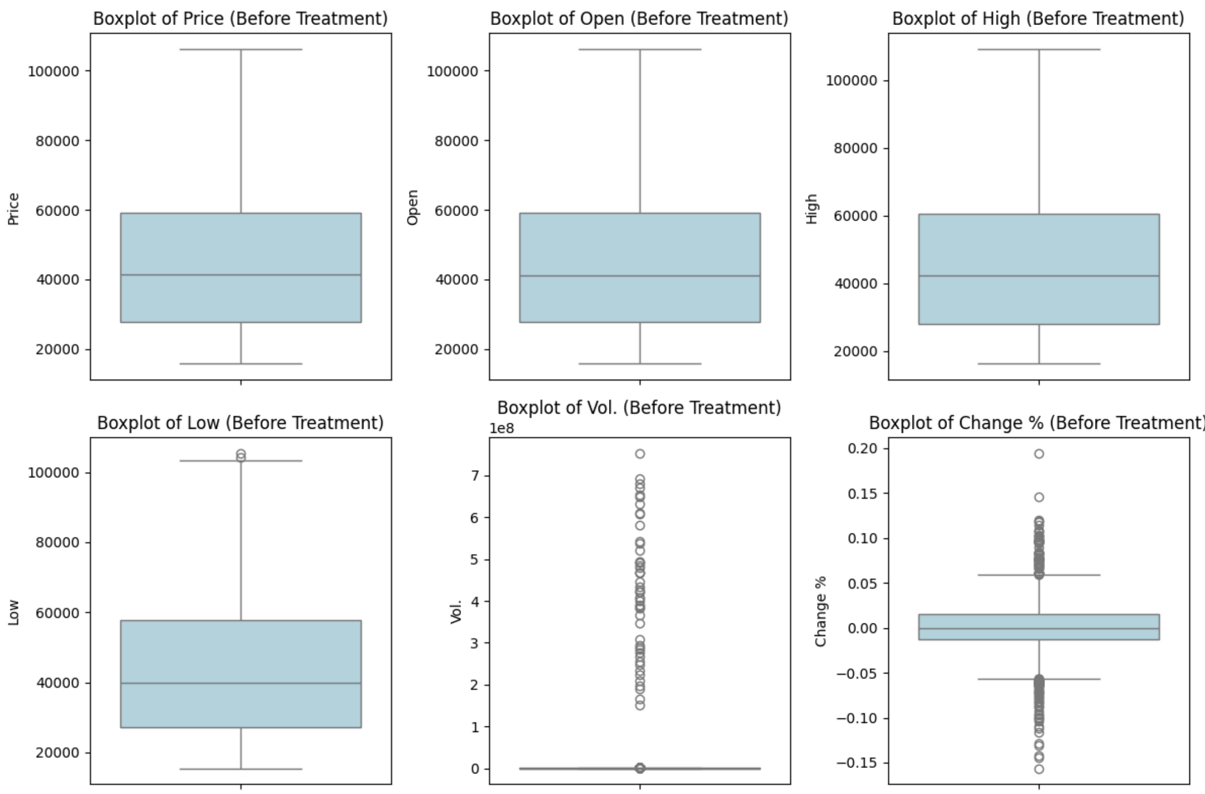
In [18]:
```
# Dataset after cleaning
df.head(10)
```

Out[18]:

	Date	Price	Open	High	Low	Vol.	Change %
0	2025-03-10	79812.1	80702.2	83902.8	79264.3	105700.0	-0.0109
1	2025-03-09	80691.6	86221.5	86498.6	80048.9	69900.0	-0.0641
2	2025-03-08	86221.9	86783.8	86886.8	85264.6	41900.0	-0.0036
3	2025-03-07	86531.2	89879.5	91059.8	84864.3	138110.0	-0.0378
4	2025-03-06	89930.9	90611.7	92802.0	87849.6	89270.0	-0.0075
5	2025-03-05	90611.7	87269.5	90937.8	86429.4	95540.0	0.0383
6	2025-03-04	87266.3	86083.8	88887.8	81617.0	132500.0	0.0123
7	2025-03-03	86209.7	94266.1	94266.1	85140.8	143150.0	-0.0855
8	2025-03-02	94265.1	86065.7	94986.5	85069.3	126760.0	0.0952
9	2025-03-01	86071.6	84353.4	86546.3	83837.3	79510.0	0.0200

Handling Outliers

In [19]:
```
# Define numerical columns to check for outliers
num_cols = ['Price', 'Open', 'High', 'Low', 'Vol.', 'Change %']

# Create boxplots to visualize outliers before treatment
plt.figure(figsize=(12, 8))
for i, col in enumerate(num_cols):
    plt.subplot(2, 3, i+1)  # Arrange subplots in a 2x3 layout
    sns.boxplot(y=df[col], color='lightblue')
    plt.title(f'Boxplot of {col} (Before Treatment)')

plt.tight_layout()
plt.show()
```



In [20]:
```python
# Function to calculate IQR and identify outliers
def identify_outliers(df, column):
    Q1 = df[column].quantile(0.25)  # 25th percentile
    Q3 = df[column].quantile(0.75)  # 75th percentile
    IQR = Q3 - Q1  # Interquartile range

    # Define the lower and upper bounds
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    # Count number of outliers
    outliers = df[(df[column] < lower_bound) | (df[column] > upper_bound)]
    print(f"{column}: {len(outliers)} outliers detected")

# Check outliers for each numerical column
for col in num_cols:
    identify_outliers(df, col)
```

```
Price: 0 outliers detected
Open: 0 outliers detected
High: 0 outliers detected
Low: 2 outliers detected
Vol.: 158 outliers detected
Change %: 121 outliers detected
```

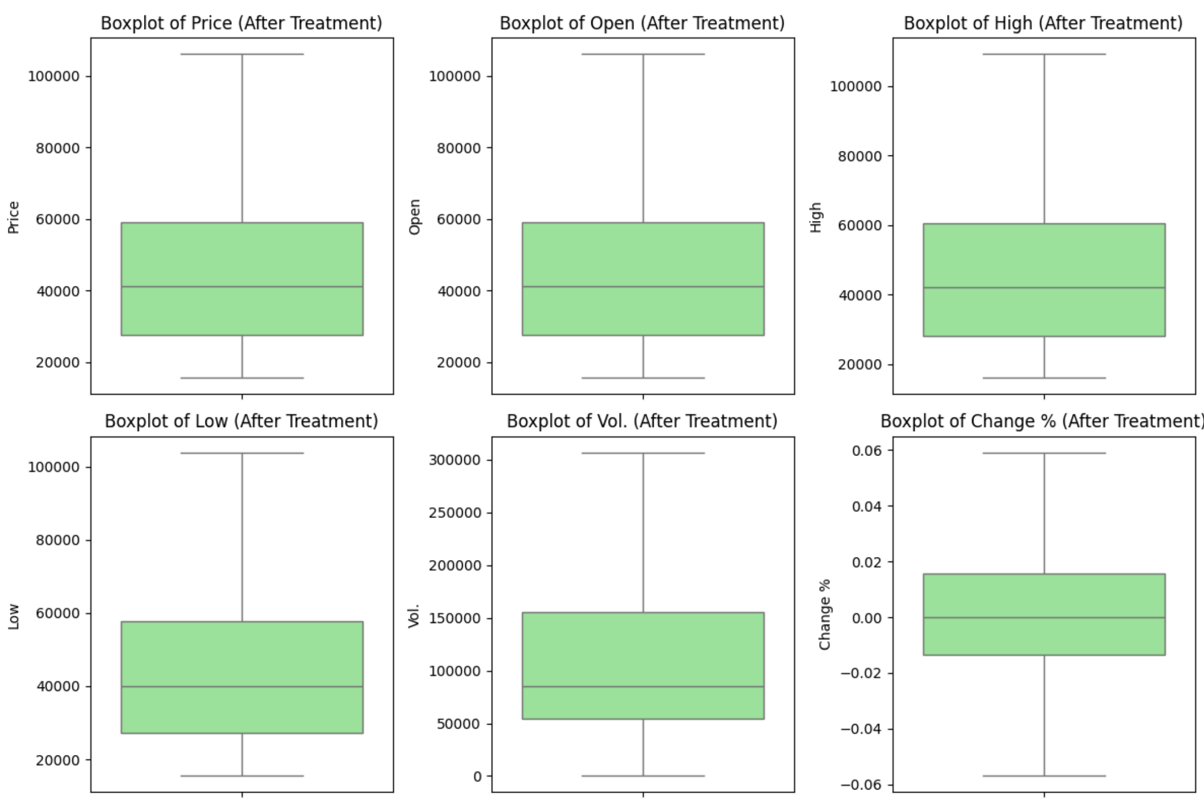
In [21]:
```python
# Function to cap outliers using IQR method
def cap_outliers(df, column):
    Q1 = df[column].quantile(0.25)  # 25th percentile
    Q3 = df[column].quantile(0.75)  # 75th percentile
    IQR = Q3 - Q1  # Interquartile range

    # Define the lower and upper bounds
```

```python
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    # Cap the values instead of removing them
    df[column] = np.where(df[column] < lower_bound, lower_bound, df[column])
    df[column] = np.where(df[column] > upper_bound, upper_bound, df[column])

# Apply capping to all numerical columns
for col in num_cols:
    cap_outliers(df, col)

# Check dataset shape after handling outliers
print("\nDataset shape after handling outliers:", df.shape)
```

```
Dataset shape after handling outliers: (1518, 7)
```

In [22]:

```python
# Create boxplots to visualize outliers after treatment
plt.figure(figsize=(12, 8))
for i, col in enumerate(num_cols):
    plt.subplot(2, 3, i+1)  # Arrange subplots in a 2x3 layout
    sns.boxplot(y=df[col], color='lightgreen')
    plt.title(f'Boxplot of {col} (After Treatment)')

plt.tight_layout()
plt.show()
```



Feature Engineering

In [23]:

```python
# Extract date-based features from 'Date' column
df['Year'] = df['Date'].dt.year  # Extract year
```

```python
df['Month'] = df['Date'].dt.month  # Extract month
df['Day'] = df['Date'].dt.day  # Extract day
df['DayOfWeek'] = df['Date'].dt.dayofweek  # Extract day of the week (0 = Mo
df['WeekOfYear'] = df['Date'].dt.isocalendar().week  # Extract week of the y

# Check new features
df.head()
```

Out[23]:

	Date	Price	Open	High	Low	Vol.	Change %	Year	Month
0	2025-03-10	79812.1	80702.2	83902.8	79264.3	105700.0	-0.0109	2025	3
1	2025-03-09	80691.6	86221.5	86498.6	80048.9	69900.0	-0.0569	2025	3
2	2025-03-08	86221.9	86783.8	86886.8	85264.6	41900.0	-0.0036	2025	3
3	2025-03-07	86531.2	89879.5	91059.8	84864.3	138110.0	-0.0378	2025	3
4	2025-03-06	89930.9	90611.7	92802.0	87849.6	89270.0	-0.0075	2025	3

In [24]:

```python
# Create a new dataframe to store engineered features
df_cleaned = pd.DataFrame(df)

# Compute percentage change in price and volume
df_cleaned['Price_Change_Percent'] = df['Price'].pct_change() * 100
df_cleaned['Vol_Change_Percent'] = df['Vol.'].pct_change() * 100
```

In [25]:

```python
# 📊 Compute 7-day and 21-day Exponential Moving Averages (EMAs)
# EMA gives more weight to recent prices, making it more responsive than a S
# Short-term EMAs (like 7-day) react faster to price changes, while long-ter

df_cleaned['Short_Term_EMA'] = df_cleaned['Price'].ewm(span=7, adjust=False)
df_cleaned['Long_Term_EMA'] = df_cleaned['Price'].ewm(span=21, adjust=False)

# Check dataset
df_cleaned.head(10)
```

Out[25]:

	Date	Price	Open	High	Low	Vol.	Change %	Year	Month
0	2025-03-10	79812.1	80702.2	83902.8	79264.3	105700.0	-0.0109	2025	3
1	2025-03-09	80691.6	86221.5	86498.6	80048.9	69900.0	-0.0569	2025	3
2	2025-03-08	86221.9	86783.8	86886.8	85264.6	41900.0	-0.0036	2025	3
3	2025-03-07	86531.2	89879.5	91059.8	84864.3	138110.0	-0.0378	2025	3
4	2025-03-06	89930.9	90611.7	92802.0	87849.6	89270.0	-0.0075	2025	3
5	2025-03-05	90611.7	87269.5	90937.8	86429.4	95540.0	0.0383	2025	3
6	2025-03-04	87266.3	86083.8	88887.8	81617.0	132500.0	0.0123	2025	3
7	2025-03-03	86209.7	94266.1	94266.1	85140.8	143150.0	-0.0569	2025	3
8	2025-03-02	94265.1	86065.7	94986.5	85069.3	126760.0	0.0591	2025	3
9	2025-03-01	86071.6	84353.4	86546.3	83837.3	79510.0	0.0200	2025	3

✅ Feature Selection

In [26]:

```
import numpy as np

# Create the binary target variable
# If today's price increased compared to yesterday, mark it as 1 (Price Up),
df_cleaned['Price_Up'] = np.where(df_cleaned['Price_Change_Percent'] > 0, 1,

# Select meaningful features based on domain knowledge and prediction releva
# These features help model the price movement trend effectively

selected_features = [
    'Open',                  # Opening price of the day
    'High',                  # Highest price of the day
    'Low',                   # Lowest price of the day
    'Vol.',                  # Volume traded — often a volatility indicator
    'Change %',              # Previous day's % change in price
    'Price_Change_Percent', # Continuous version of the target (momentum)
    'Short_Term_EMA',        # 7-day exponential moving average (short-term t
    'Long_Term_EMA',         # 21-day exponential moving average (long-term t
    'DayOfWeek',             # Day of the week — might impact trading behavio
    'Month'                  # Month of the year — seasonal market effects
]
```

```
# Target variable for logistic regression
target_variable = 'Price_Up'

# Prepare a cleaned dataframe with only selected features + target
df_features = df_cleaned[selected_features + [target_variable]].dropna()

# Preview the resulting feature set
print("Selected Features:")
df_features.head()
```

Selected Features:

Out[26]:

	Open	High	Low	Vol.	Change %	Price_Change_Percent	Short_T
1	86221.5	86498.6	80048.9	69900.0	-0.0569	1.101963	800
2	86783.8	86886.8	85264.6	41900.0	-0.0036	6.853625	815
3	89879.5	91059.8	84864.3	138110.0	-0.0378	0.358726	828
4	90611.7	92802.0	87849.6	89270.0	-0.0075	3.928872	845
5	87269.5	90937.8	86429.4	95540.0	0.0383	0.757026	860

✅ Data Visualization

1️⃣ Price over Time – Long-term trend

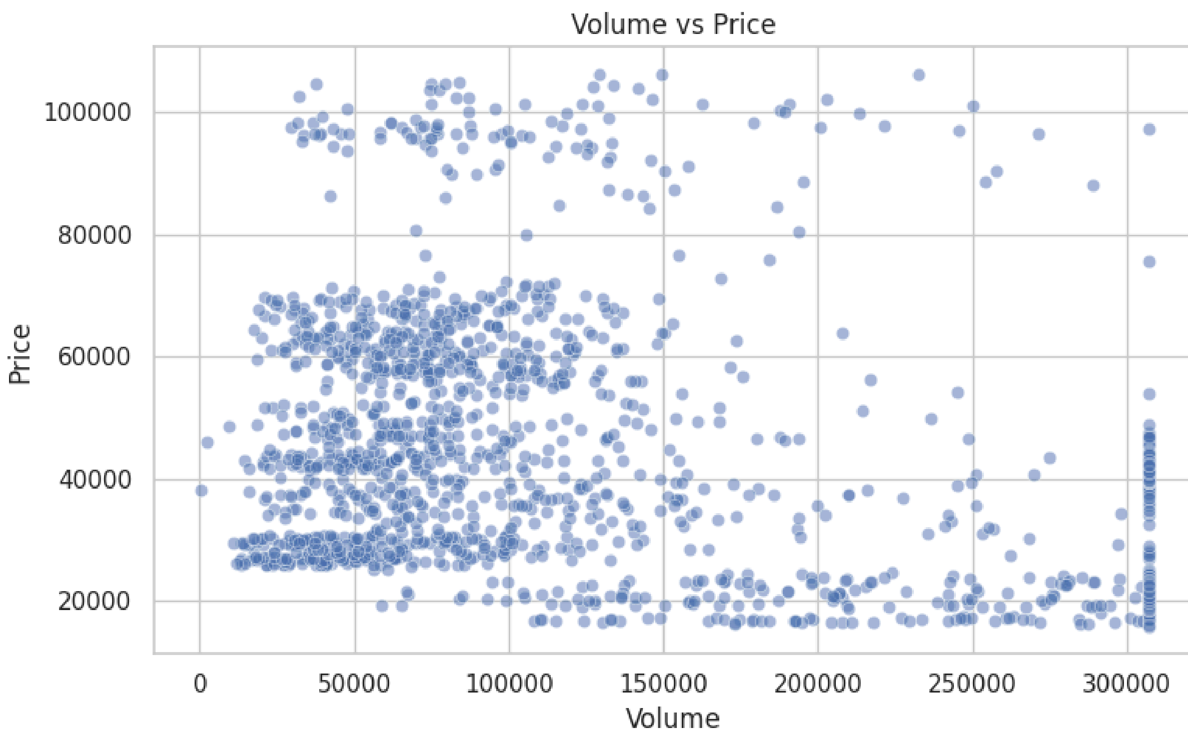
In [27]:

```
sns.set(style='whitegrid')
plt.figure(figsize=(12, 5))
plt.plot(df_cleaned['Date'], df_cleaned['Price'], color='orange')
plt.title('Bitcoin Price Over Time')
plt.xlabel('Date')
plt.ylabel('Price (USD)')
plt.tight_layout()
plt.show()
```

The price of Bitcoin shows high volatility with several boom and bust cycles. It has shown long-term growth with sharp corrections in between.

2️⃣ Volume vs Price – Check how volume influences price

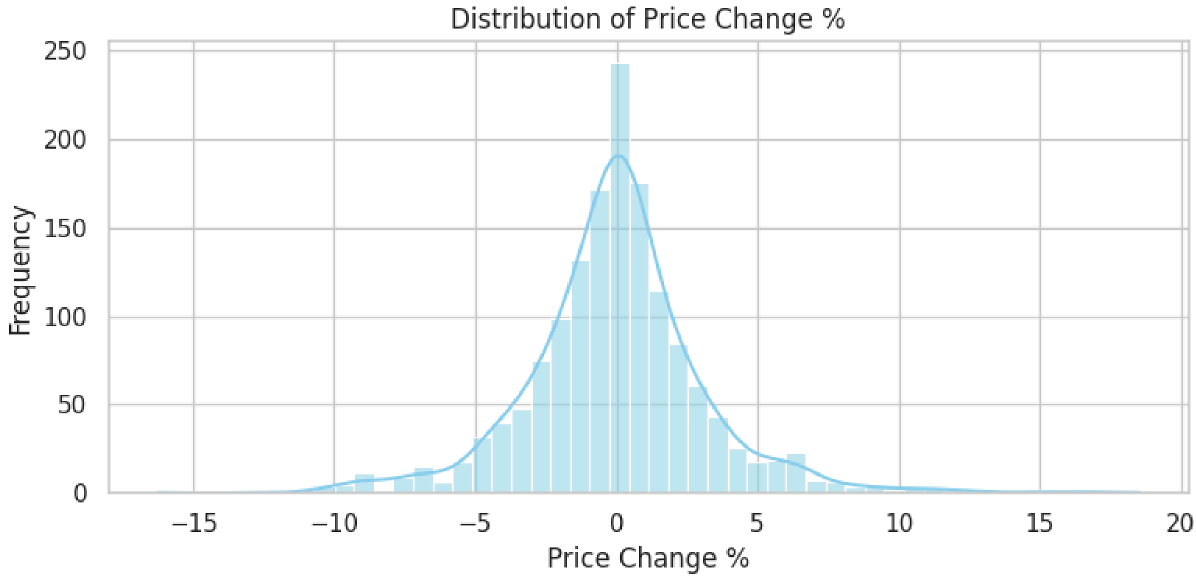
In [28]:
```
plt.figure(figsize=(8, 5))
sns.scatterplot(data=df_cleaned, x='Vol.', y='Price', alpha=0.5)
plt.title('Volume vs Price')
plt.xlabel('Volume')
plt.ylabel('Price')
plt.tight_layout()
plt.show()
```



There is no strong relationship between trading volume and Bitcoin price. Price remains highly variable even with high volume levels.

3️⃣ Price Change % Distribution – Understand target behavior

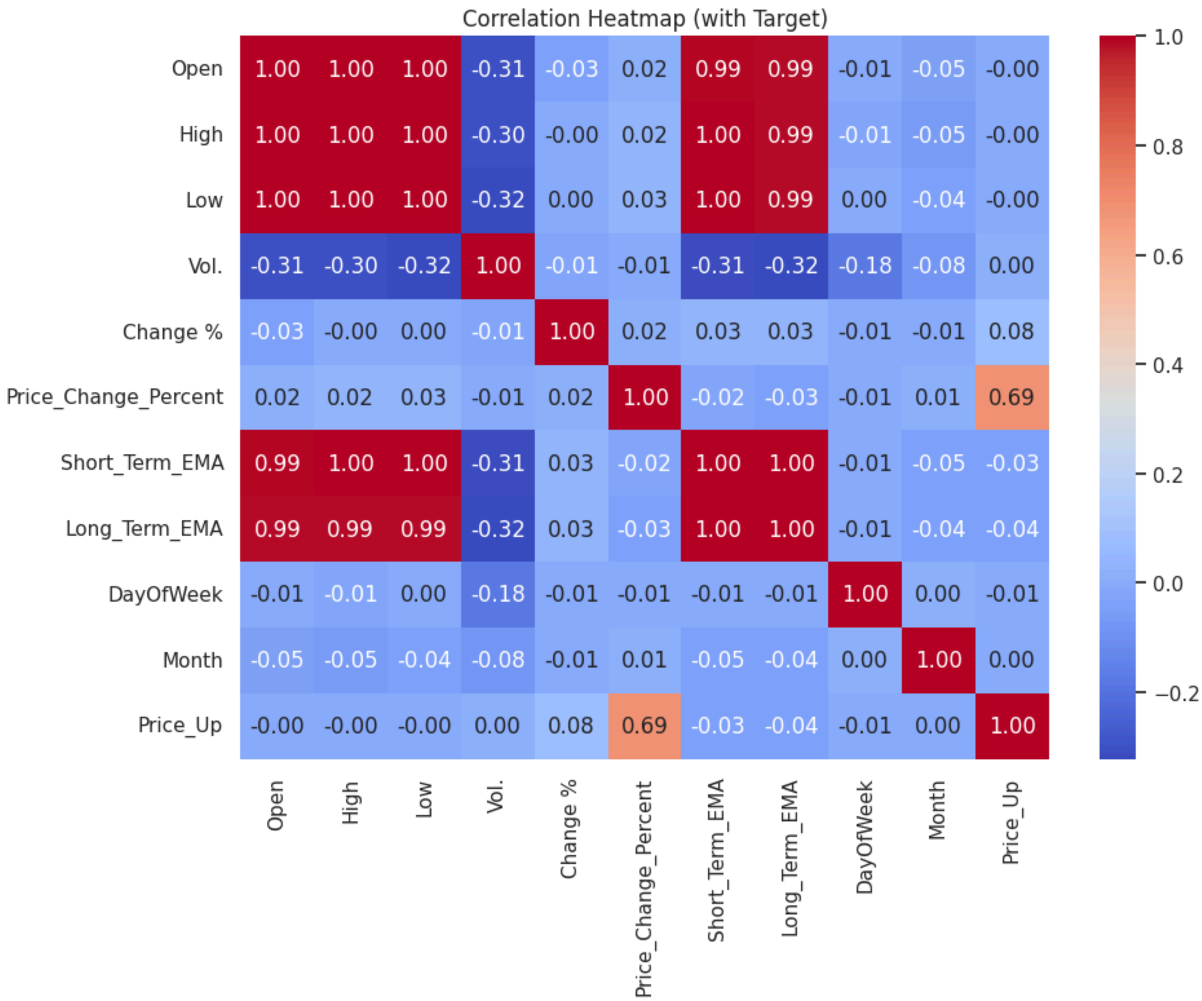
In [29]:
```
plt.figure(figsize=(8, 4))
sns.histplot(df_cleaned['Price_Change_Percent'], bins=50, kde=True, color='s
plt.title('Distribution of Price Change %')
plt.xlabel('Price Change %')
plt.ylabel('Frequency')
plt.tight_layout()
plt.show()
```



Most daily price changes are centered around 0%, forming a near-normal distribution. However, there are outliers indicating occasional high volatility.

4️⃣ Correlation Heatmap – Find top features linked with target

In [30]:
```
df_cleaned['Price_Up'] = np.where(df_cleaned['Price_Change_Percent'] > 0, 1,
selected_for_corr = [
    'Open', 'High', 'Low', 'Vol.', 'Change %',
    'Price_Change_Percent', 'Short_Term_EMA', 'Long_Term_EMA',
    'DayOfWeek', 'Month', 'Price_Up'
]
plt.figure(figsize=(10, 8))
sns.heatmap(df_cleaned[selected_for_corr].corr(), annot=True, cmap='coolwarm
plt.title('Correlation Heatmap (with Target)')
plt.tight_layout()
plt.show()
```

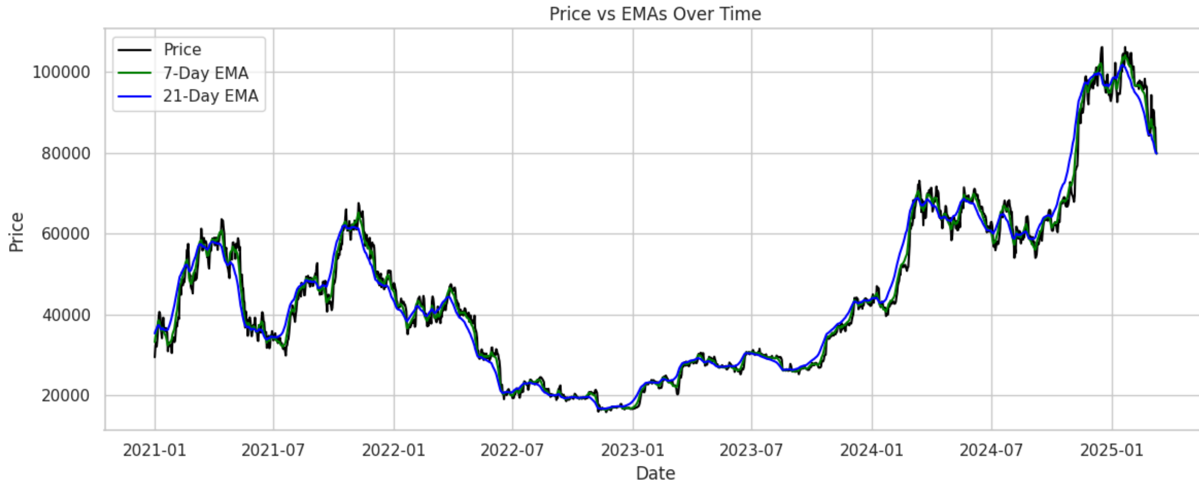


Price_Change_Percent has the strongest positive correlation with the target variable Price_Up. Volume and temporal features like DayOfWeek and Month show weak correlations.

5️⃣ EMAs vs Price – See if EMAs capture trend direction

In [31]:

```
plt.figure(figsize=(12, 5))
plt.plot(df_cleaned['Date'], df_cleaned['Price'], label='Price', color='blac
plt.plot(df_cleaned['Date'], df_cleaned['Short_Term_EMA'], label='7-Day EMA'
plt.plot(df_cleaned['Date'], df_cleaned['Long_Term_EMA'], label='21-Day EMA'
plt.title('Price vs EMAs Over Time')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend()
plt.tight_layout()
plt.show()
```



Bitcoin price tracks closely with short and long-term EMAs. EMA crossovers can act as indicators of trend reversals or momentum shifts.

✅Model Building

In [32]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

In [33]:
```
# Features and target for regression
X = df_features.drop(columns=['Price_Change_Percent', 'Price_Up'])
y = df_features['Price_Change_Percent']

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar
```

In [34]:
```
# Initialize and train model
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)
```

Out[34]:

```
▾ LinearRegression
LinearRegression()
```

In [35]:
```
# Predictions
y_pred = lr_model.predict(X_test)

# Evaluate performance
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)

print("📊 Linear Regression Performance:")
print(f"Mean Squared Error (MSE): {mse:.4f}")
```

```python
print(f"Root Mean Squared Error (RMSE): {rmse:.4f}")
print(f"R-squared Score (R²): {r2:.4f}")
```

```
📊 Linear Regression Performance:
Mean Squared Error (MSE): 5.8701
Root Mean Squared Error (RMSE): 2.4228
R-squared Score (R²): 0.4160
```

In [36]:
```python
plt.figure(figsize=(8, 5))
plt.scatter(y_test, y_pred, alpha=0.5, color='teal')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')
plt.xlabel('Actual Price Change %')
plt.ylabel('Predicted Price Change %')
plt.title('Actual vs Predicted: Price Change % (Linear Regression)')
plt.tight_layout()
plt.show()
```